YIELD VARIABILITY AS INFLUENCED BY CLIMATE: A STATISTICAL INVESTIGATION *

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Abstract. One of the issues with respect to climate change involves its influence on the distribution of future crop yields. Many studies have been done regarding the effect on the mean of such distributions but few have addressed the effect on variance. Furthermore, those that have been done generally report the variance from crop simulators, not from observations. This paper examines the potential effects of climate change on crop yield variance in the context of current observed yields and then extrapolates to the effects under projected climate change. In particular, maximum likelihood panel data estimates of the impacts of climate on year-to-year yield variability are constructed for the major U.S. agricultural crops. The panel data technique used embodies a variance estimate developed along the lines of the stochastic production function approach suggested by Just and Pope. The estimation results indicate that changes in climate modify crop yield levels and variances in a crop-specific fashion. For sorghum, rainfall and temperature increases are found to increase yield level and variability. On the other hand, precipitation and temperature are individually found to have opposite effects on corn yield levels and variability.

1. Introduction

Inter-annual variability of agricultural yields is well known to depend on the weather. Extreme weather events like hurricanes and droughts have had obvious impacts on annual harvests, recently motivating two disaster relief bills for farmers. More subtle seasonal phenomena also have been linked to agricultural productivity, with Florida citrus freeze risk (Downton and Miller, 1993), and dryland maize production in southern Africa having been shown to be influenced by El Niño Southern Oscillation (ENSO) and other ocean circulation patterns (Cane et al., 1994). Identification and prediction of the influences of seasonal-to-interannual climate phenomena like ENSO, has brought attention to the impacts of year-to-year

* Seniority of authorship is shared. This research was partially supported by and is a contribution to the National Assessment of Climate Change, Agricultural Focus Group, supported by the U.S. Global Climate Change Office. The views expressed are not necessarily those of the U.S. Department of Agriculture.

Climatic Change **66:** 239–261, 2004.

fluctuations in climate. Some of the agricultural policy questions that are raised are related to increases in farm size, access to farm support programs, and risk spreading. In the design of farm programs and disaster relief legislation it may be useful for policymakers and analysts to know if policies address intermittent conditions or if changes in agricultural production technology and climate might be expected to more permanently affect crop yield variability.

The considerable attention that has been devoted to climate change impacts on agriculture has largely focused on fifty to 100 year mean climate change effects on average levels of crop yields (Lewandrowski and Schimmelpfennig, 1999; Adams et al., 1998). Crop yield variability has been considered in a few longer term cases, but these studies do not generally incorporate sensitivity tests or estimate changes in distributions of outcomes (Mearns et al., 1996, 1997; Schimmelpfennig, 1996).

Factors other than climate are known to influence crop yield variability. Anderson and Hazell (1987) argue that adoption of common high-yielding varieties, uniform planting practices, and common timing of field operations have caused yields of many crops to become more strongly influenced by weather patterns, especially in developing countries. Hazell (1984) makes similar observations concerning cereal production in the United States. Roumasset et al. (1987) and Tollini and Seagraves (1970) argue that increased fertilizer use has had an impact. Hurd (1994) analyzes the effect of yield variability on the adoption of integrated pest management in a heteroskedastic production model like our own.

An open question is how sensitive is inter-annual crop yield variability to climatic change? The ultimate answer will depend upon future technological progress, crop-climatic adaptation, and CO_2 fertilization effects among many other factors. These factors are difficult to model, but a current statistical answer can be obtained from historical records relating crop yield variability to climate. To address this we pool time-series and cross-sectional data including climate variables in an approach much like that employed by Mendelsohn et al. (1994) to measure inter-annual yield variability impacts of shifts in climate. Specifically, we examine data for U.S. corn, cotton, sorghum, soybeans, and wheat yields to see how they are affected by climate conditions. In turn, we apply the estimation results to the climate projections arising from the Hadley and Canadian General Circulation Models (GCM) as used in the U.S. Global Climate Research Program's (US GCRP) National Assessment to develop estimates of the magnitude of the climate change effect on crop yield variation.

Our results should help policymakers and stakeholders evaluate future agricultural policy objectives such as rural income maintenance. Farm income and crop insurance programs might be influenced by both mean agricultural productivity and crop yield variability. Plant breeders have worked to increase average crop yields through traditional plant breeding and biotechnology, which has increased the speed of innovation, but these developments might also have caused yield variability to increase which would allow us to use statistical data to consider possible future climatic effects on variability.

2. Background on the Method

Just and Pope (1978) developed a stochastic production function specification that allows explicit estimation of the effects of independent variables on the probability distribution of output (p. 79). An added advantage of the approach is that it does not impose dependence between an item's effect on yield variability and its effect on mean yield. Just and Pope (1978, 1979) described both a Maximum Likelihood (MLE) (1978) and a three step, feasible generalized least squares (FGLS) (1979) procedure for estimating the function.

Antle (1987) extended Just and Pope's (1978, 1979) approach by developing a moment-based stochastic production function that is used to estimate higher order moments and subsequently a set of input demand functions and a distribution of risk preferences. Love and Buccola (1991) applied related techniques to primal risk models, allowing joint estimation of either technology and yield variability or input demands and yield variability. Saha et al. (1994) showed how to jointly estimate risk preferences and the production technology. Buccola and McCarl (1986) investigated the small-sample properties of Just and Pope's (1978, 1979) three stage method, using Monte Carlo experiments. McCarl and Rettig (1983) used the three step approach to examine the effects of changes in ocean conditions on the variability of the salmon catch.

Despite the fact that Just-Pope production functions have traditionally been estimated by the three-step FGLS approach, Saha et al. (1997) show that MLEs are more efficient and unbiased than FGLS estimates for small samples in Monte Carlo experiments. There are apparently systematic errors associated with the FGLS procedure, producing understated estimates of the risk effects of inputs, a serious problem in the present context.

3. Panel Data Set for Estimation

To gain information on the inter-annual effects of climate we use annual observations across the U.S. states on crop yields and associated climate. Exploratory data analysis indicated that differences between the variability of yields for individual crop varieties were minor. There were trends in yields toward an increase in variability particularly for corn, but also for the other crops, and we control for this through our allowance for technology change. All of the corn varieties that we examined were more variable than the next most variable crop, which was soybeans. State level aggregation was chosen for the crops because of the availability of multiple years of yield data. We encountered few missing observations over the relevant time period for each crop, and of course not all states grow all of the crops.

Our estimates of inter-annual yield variability contrast with the earlier literature on crop variability that estimated distributions of crop yields within a year because those distributions were shown to change from year-to-year depending on the circumstances (Park and Sinclair, 1993; Kaylen and Koroma, 1991). For a longer-term relationship, such as those considered for climate change, state-level average climate over the growing season most accurately reflects annual growing conditions for each crop by state.* State-level climate data were drawn from the NOAA Internet home page. The temperature data are predominantly April to November averages for the relevant weather stations in a state. For regions growing mainly winter wheat, we used the November to March average temperature. The rainfall data are annual totals, reflecting both precipitation falling directly on a crop and also inter-seasonal water accumulation.

Matching agricultural output data are state-level yields and acreage harvested for 1973 to 1997 taken from USDA-NASS *Agricultural Statistics* for the contiguous 48 states. This provides between 1200 and 1400 observations for each of the various crops. Our approach makes it necessary to control for factors, other than climate, that change over time and we control for technological change with a deterministic trend, only after removing stochastic trends from the data. Moss and Shonkwiler (1993) have shown that stochastic trends can be used to model central tendency in crop yield distributions, so it is important to carefully characterize both stochastic and deterministic trends.

4. Time Series Estimation

The Just-Pope production function can be estimated from panel data relating annual yield to exogenous variables. This procedure produces estimates of the impacts of the exogenous variables on levels and the variance of inter-annual yield. An assumption of the model is that the included variables are stationary. Deterministic and stochastic trends in variables can introduce spurious correlations between the variables, because the errors in the data-generating-processes for different series might not be independent (Granger and Newbold, 1974). In other words, correlations might be detected between variables even though they are increasing for different reasons and in increments that are uncorrelated (Banerjee et al., 1993, p. 71).

An early method for accounting for the trends in many economic time series was to include a deterministic time trend. Unfortunately, correlations between variables may still be spurious even when deterministic time trends are taken into account. To make matters worse, standard t-statistics on the time trend variable are inflated when the other variables are non-stationary (Phillips, 1986). This might make it seem that a time trend is properly accounted for when it is not. The solution to these

* A potential shortcoming of this approach is that particular (agricultural) regions within a state may experience consistently different temperatures and precipitation than state averages. It is also possible that for larger growing regions (including several states) conditions might be expected to be different on the edges of the region than in the middle of the region and state-level data might fail to distinguish some of these fringe effects.

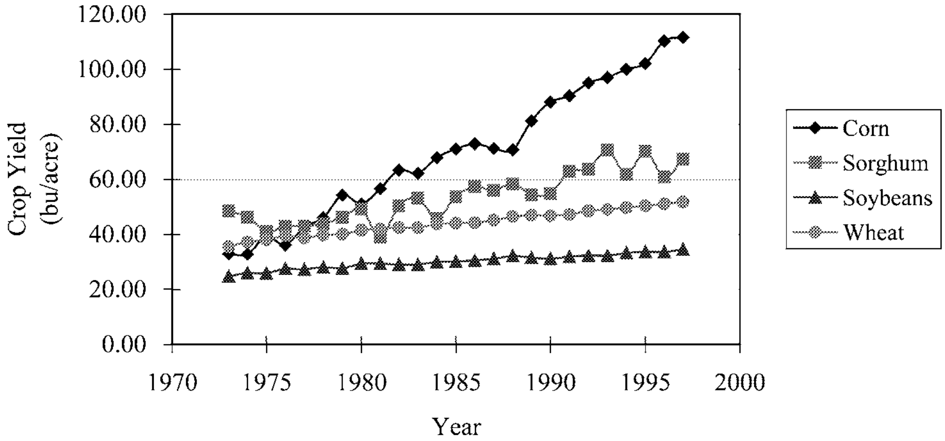

Figure 1. Average crop yield by year.

problems is to first test for stationarity. Non-stationary variables can be differenced once and retested. If the differenced versions are stationary, the variables are said to be integrated order one or $I(1)$. Stationary time series are integrated order zero or $I(0)$. Regressions on stationary variables may satisfy ideal conditions, and inferences on a deterministic time trend can be made safely. Even though there are more regions than annual observations in our data, any data set with a time dimension of 20 years or more should probably be tested for its time series properties before being used in empirical models that assume stationary variables.

Practitioners have tested for unit roots and used differencing or other filtering techniques to make their variables stationary. Until recently the time-series characteristics of a panel of data has been difficult to characterize. The observations on one or more regions in a panel could be non-stationary when considered alone, but with panel data models all of the regions are generally taken together. The concern has been about how to characterize the time series properties of one variable made up of many regions. New tests are available that offer more power than earlier tests on regional series. These new tests for stationarity are applied to each variable taking the whole panel at once. This avoids possibly conflicting time series information on regions in the panel. There are several versions of these so-called panel unit root tests that can account for the positive trends in the yields of these crops shown in Figure 1, and they are discussed in Appendix A. An upshot of the observed trends is that absolute variability is more consistent than if mean yields fluctuated both positively and negatively, in which case it would probably be necessary to consider relative variability.*

* We thank one of the referees for raising the relative variability issue.

4.1. PANEL UNIT ROOT TEST RESULTS

Im et al. (1997) propose a series of unit root test statistics in dynamic heterogenous panels based on individual Dickey-Fuller (Dickey and Fuller, 1981) regressions. The panel is dynamic because unit root tests involve inference on lags of the dependent variable. The test statistic is based on the mean of individual unit root statistics and the details of the procedure are described in Appendix A. The results in Table I come from applying the panel unit root test procedure to each individual potential dependent (yield) and independent variable (acreage, rainfall, and temperature). Table I shows that for corn, cotton, sorghum, soybeans, and wheat, the variables are stationary as a panel, i.e., integrated order zero ($I(0)$), rejecting the null hypothesis of a unit root.

There are several variations of these tests that we also performed. A slightly modified test is described by Im et al. (1997) that is robust to serial correlation. This test gives the same stationary vs. non-stationary results and we do not pursue the autocorrelation question further until we specify the production function. Another modification to our original test, based on de-meaned variables in each panel, yields slightly different results. Since the de-meaned version of the test is robust to correlation across regions, we concluded that there may be correlation across regions affecting the simpler model results, although this not a definitive test of inter-regional correlation. We will show the existence of random region effects in the production functions that we estimate in the next section. We proceed by differencing the non-stationary variables indicated by this last test (sorghum yield, cotton precipitation, and soybean temperature). These differenced variables were re-tested and the results are also in Table I (second row in a cell when there are two rows) and are shown to be stationary, i.e., $I(0)$, eliminating the possibility that any of the variables might have been integrated order two, i.e., $I(2)$.

These panel time series characteristics of the data are used in formulating the estimation approach. While it might be plausible, even if a little surprising, that some of the temperature and precipitation variables have long-term trends while some of the yield variables do not, interpretation of these results should be undertaken only after additional testing. Our concern is that stationary versions of all of the variables are used in the panel production function model in the next section. This avoids possible spurious correlations between variables and allows the establishment of valid relationships. In addition, this allows inclusion of a deterministic time trend in the production model that does not suffer from an inflated t-statistic.

4.2. THE MLE APPROACH TO ESTIMATING THE PRODUCTION FUNCTION

The previous sections established stationarity of the variables and random region effects are determined to exist from applying the procedure in Appendix B. Neither of these results rule out the possibility of deterministic trends. These results do practically rule out spurious correlations between regional yields and the climate variables because each of the variables are random walks (after differencing be-

Table I
Unit root test results

	Yield	Acre (planted acreage)	Precipitation	Temperature
No-serial correlation				
Corn	13.87 [a]	65.08 [a]	73.17 [a]	125.88 [a]
Cotton	14.48 [a]	35.38 [a]	83.74 [a]	81.18 [a]
Sorghum	14.83 [a]	51.34 [a]	91.02 [a]	88.42 [a]
Soybeans	34.37 [a]	52.39 [a]	56.73 [a]	104.00 [a]
Wheat	27.77 [a]	46.82 [a]	73.38 [a]	128.81 [a]
Serial correlation				
Corn	–4.86 [a]	64.37 [a]	63.88 [a]	126.07 [a]
Cotton	6.86 [a]	32.98 [a]	67.63 [a]	84.13 [a]
Sorghum	–2.26 [a]	70.22 [a]	81.82 [a]	89.58 [a]
Soybeans	6.92 [a]	63.06 [a]	49.45 [a]	101.26 [a]
Wheat	2.31 [a]	50.88 [a]	64.19 [a]	126.20 [a]
Correlation across groups				
Corn	2.79 [a]	–3.72 [a]	7.10 [a]	9.92 [a]
Cotton	35.13 [a]	–5.69 [a]	0.79 28.22 [a]	1.91 [a]
Sorghum	0.55 10.40 [a]	–3.34 [a]	2.54 [a]	2.21 [a]
Soybeans	8.17 [a]	–6.98 [a]	5.53 [a]	–0.48 499.13 [a]
Wheat	8.15 [a]	–7.02 [a]	7.05 [a]	10.36 [a]

Table I reports three versions of Im et al.'s LM-bar test statistic. 'Serial correlation' statistics are robust to error term serial correlation, while 'correlation across groups' statistics are robust to serial correlation in the cross-section dimension. When there are two statistics in a cell, the top number is for the test on the undifferenced variable, and the bottom number is for the test on the variable after it has been differenced once.
[a] Null hypothesis of non-stationarity is rejected with 99% confidence.

cause they are stationary) and the regional effects are random. Another factor to consider is that crop yield variability (see Figure 2) appears to be increasing for corn but not for soybeans. Following Saha et al. (1997), we proceed by estimating production functions of the form

$$y = f(X, \beta) + h(X, \alpha)\varepsilon\,, \tag{1}$$

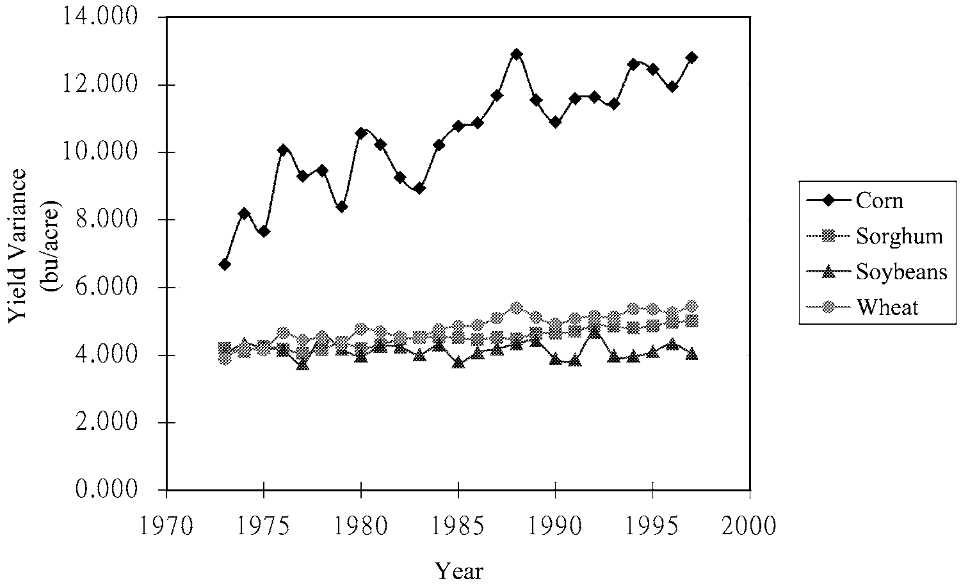

Figure 2. Crop yield variability by year.

where y is crop yield (corn, cotton, sorghum, soybeans, and wheat), $f(\cdot)$ is an average production function, and X is a set of independent explanatory variables (climate, location, and time period). The functional form $h(\cdot)$ for the error term is an explicit form for heteroskedastic errors, allowing estimation of variance effects. Estimates of the parameters of $f(\cdot)$ give the average effect of the independent variables on yield, while $h^2(\cdot)$ gives the effect of each independent variable on the variance of yield. The interpretation of the signs on the parameters of $h(\cdot)$ is straightforward. If the marginal effect on yield variance of any independent variable is positive, then increases in that variable increase the standard deviation of yield, while a negative sign implies increases in that variable reduce yield variance.

The log-likelihood function is then:

$$\ln L = -\frac{1}{2}\left[n * \ln(2\pi) + \sum_{i=1}^{n} \ln(h(X_i, \alpha)^2) + \sum_{i=1}^{n} \frac{(y_i - f(X_i, \beta))^2}{h(X_i, \alpha)^2}\right]. \quad (2)$$

Due to advances in non-linear optimization procedures, the parameters α and β can be estimated in a single-stage maximization of (2), under the assumptions that $y_i \sim N(f(X_i, \beta), h(X_i, \alpha)^2)$ and $\varepsilon_i \sim N(0, 1)$.

4.3. CROP YIELD PRODUCTION FUNCTION ESTIMATES

After controlling for random effects, the MLEs of the $f(X, \beta)$ portion of the crop production functions can be estimated and are displayed in Table III. Two specifications are tested, linear and Cobb-Douglas, and for precipitation and temperature for

Table II
Panel model specification tests

	Corn	Cotton	Sorghum	Soybeans	Wheat
Fixed vs. random effects	15.37 [a]	6.44 [a]	7.52 [a]	14.45 [a]	12.06 [a]
Serial correlation	0.87 [b]	0.81 [b]	1.22 [b]	1.23 [b]	0.18 [b]
Range of normality statistics across states	0.29–3.24 [c]	0.01–93.6	0.05–6.65 [c]	0.08–2.25 [c]	0.11–2.74 [c]

[a] Null hypothesis is rejected with 99% confidence.
[b] Fails to reject the null hypothesis of no serial correlation with 99% confidence.
[c] Rejects the null hypothesis of non-normality with 99% confidence. The range is the minimum and the maximum of the Wald test statistics across all states represented in the data set. A more detailed table with skewness, kurtosis, and Wald statistics by state is available from the authors upon request.

corn, cotton and sorghum these forms give similar results. The sign on precipitation is positive for all three crops and is negative on temperature. This indicates that crop yields increase with more rainfall and decrease with higher temperatures, holding acreage constant and after controlling for a deterministic time trend that may serve as a proxy for the non-stochastic portion of the advance of agricultural technology.

Higher temperatures positively affect soybean yields (Cobb-Douglas estimate insignificant) and negatively affect wheat yields. The coefficients on the deterministic time trend are positive and significant as expected for all crops, except the Cobb-Douglas estimates for cotton and wheat. This may come from the tendency of Cobb-Douglas functional forms to pick up curvature because they are non-linear over a wide range of parameter values, and may indicate a declining rate of increase in the effect of technology on yield rather than an actual negative impact of technology.*

The coefficients for rainfall and temperature can be converted to elasticities by multiplying by sample average climate and dividing by average yield. These elasticities are reported in Table IV. For corn yields, the percentage effects of changes in climate estimated from the Cobb-Douglas functional form are higher than the linear estimates. Elasticities for the other crops are mixed, with uniformly high elasticities being measured for both rainfall and temperature on sorghum. Tests of

* Future research will investigate the extent of these non-linear effects by considering quadratic and flexible functional form estimates for the entire sample and for regional sub-samples. Until this further work on non-linear response of variability to climate is completed, these Cobb-Douglas estimates should probably be considered as simply providing verification of the linear results (in most cases).

Table III

Estimated parameters for average crop yield production functions ($f(X, \beta)$) under linear and Cobb-Douglas functional forms

	Acre	Precipitation	Temperature	Year	Constant	Log-likelihood
Corn						
Linear	0.0146 [a]	0.9265 [a]	–0.3843 [a]	3.3018 [a]	0.4430	–19169240
	(0.00039)	(0.00606)	(0.01599)	(0.06492)	(0.9978)	
Cobb-Douglas	1.0728 [a]	1.5148 [a]	–2.9792 [a]	2.0470 [a]	0.0560 [a]	0.00
	(0.00105)	(0.00160)	(0.00064)	(0.00061)	(0.00007)	
Cotton						
Linear	–0.00010 [a]	0.00679 [a]	–0.02731 [a]	0.02107 [a]	2.8990 [a]	–106332
	(0.000001)	(0.00010)	(0.00035)	(0.00014)	(0.02524)	
Cobb-Douglas	0.30879 [a]	0.40751 [a]	–0.74763 [a]	–0.31626 [a]	2.6774 [a]	0.00
	(0.00736)	(0.01812)	(0.02059)	(0.01382)	(0.01618)	
Sorghum						
Linear	0.00042 [a]	0.05786 [a]	–0.02242 [a]	0.10573 [a]	–1.4303 [a]	–793264
	(0.00002)	(0.00086)	(0.00281)	(0.00186)	(0.19234)	
Cobb-Douglas	0.3895 [a]	1.8977 [a]	–2.6070 [a]	1.3758 [a]	0.2610 [a]	0.00
	(0.02159)	(0.03633)	(0.04189)	(0.02864)	(0.01441)	
Soybeans						
Linear	0.00149 [a]	–0.16234 [a]	0.00386 [a]	0.34695 [a]	29.865 [a]	–1636508
	(0.000006)	(0.00082)	(0.00037)	(0.00145)	(0.04464)	
Cobb-Douglas	0.1558 [a]	0.3640 [a]	0.0016	0.2113 [a]	1.5992 [a]	0.00
	(0.00086)	(0.00267)	(0.00149)	(0.00159)	(0.00351)	
Wheat						
Linear	0.00130 [a]	–0.15262 [a]	–0.33372 [a]	0.63271 [a]	60.371 [a]	–7505439
	(0.000004)	(0.00054)	(0.00145)	(0.00094)	(0.08986)	
Cobb-Douglas	0.03485 [a]	1.4178 [a]	–0.37209 [a]	–0.23611 [a]	1.6014 [a]	0.00
	(0.01337)	(0.03053)	(0.00613)	(0.01605)	(0.00364)	

Numbers in parentheses are standard errors.

[a] Significant at 99% confidence level.

Table IV

Elasticity of average crop yield to a change in precipitation or temperature

Production function form	Corn		Cotton		Sorghum		Soybean		Wheat	
	Precipitation	Temperature	Precipitation	Temperature	Precipitation	Temperature	Precipitation	Temperature	Precipitation	Temperature
Linear	0.3273	–0.2433	0.0371	–1.5334	2.8844	–2.0866	–0.2068	0.0002	–0.1309	–0.5076
Cobb-Douglas	1.5148	–2.9792	0.4075	–0.7476	1.8977	–2.6070	0.34640	N.S.	1.4178	–0.3721

Linear elasticities are coefficients in Table III multiplied by average climate divided by average yield (see Figure 1).
N.S. – not significant.

model adequacy were carried out and are described in Appendix C. Estimates of the impact of climate variability on crop yields are presented in the next section.

5. Variability Results from the Estimated Model

The operative empirical question that can be addressed given the above results involves the way that crop yield variability responds to changes in temperature and precipitation. The clearest results are those for corn, cotton and sorghum where we find results that are independent of functional form (Table V). In those cases increases in rainfall decrease yield variability for corn and cotton, but increase it for sorghum. Simultaneously, higher temperatures decrease the variance of cotton and sorghum yields, but increase variability for corn. Such results are not surprising if one looks at the characteristics of the physical locations of these crops coupled with common crop cultural conditions. Corn is grown best in more temperate zones and has high water requirements. Yields in hotter drier conditions are generally lower and more variable as the estimation confirms. Sorghum is generally grown in higher temperature lower rainfall conditions, and the results show lower temperatures or more rainfall increase variability. Cotton is grown in the hotter but often more humid areas of the Southern U.S., again a fact not inconsistent with the finding that variability increases as temperature and rainfall are reduced.

Elasticities giving the percentage increase in variability for a percent increase in rainfall and temperature variability are reported in Table VI. Cotton and sorghum rainfall variability elasticities are all small, with a one percent increase in rainfall leading to a half of one percent or less increase or decrease in yield variability. Cotton and sorghum have high temperature variance elasticities with a one-percent change in temperature leading to an up to eleven percent decrease in yield variability. Similarly large elasticities are obtained for rainfall effects on corn and wheat yield variability. Elasticities for corn, cotton, sorghum and wheat have the same sign across functional forms. Soybean elasticities are less than one, but the signs are inconsistent across functional forms making these results harder to interpret. The distinction between the impacts of climate on levels and variance of yields raises several policy questions related to crop insurance and climate change assessment that will be addressed in the next several sections.

5.1. POTENTIAL EFFECT OF PROJECTED CLIMATE CHANGE

To gauge the potential effect on yield variability of currently projected climate change, we use the climate change projections for 2090 from the U.S. Global Climate Change Research Program's National Assessment. Those projections were developed using the Canadian and Hadley global circulation models (for details see USGCRP). Each projection includes specific changes in regional precipitation and temperature which were in turn plugged into the Cobb-Douglas functional form of

Table V

Estimated parameters for crop yield variability functions ($h(X, \alpha)$) under linear and Cobb-Douglas functional forms

	Acre	Precipitation	Temperature	Year	Constant
Corn					
Linear	0.0005 [a]	–0.2720 [a]	0.1172 [a]	0.2052 [a]	9.4197 [a]
	(0.000002)	(0.00070)	(0.00105)	(0.00217)	(0.0555)
Cobb-Douglas	0.4711 [a]	–1.4461 [a]	0.8923 [a]	0.1356 [a]	2.2785 [a]
	(0.00116)	(0.00284)	(0.11526)	(0.00019)	(0.4744)
Cotton					
Linear	–0.00007 [a]	–0.04405 [a]	–0.15506 [a]	0.03161 [a]	9.2579 [a]
	(0.000005)	(0.00068)	(0.00095)	(0.00052)	(0.06642)
Cobb-Douglas	0.2537 [a]	–0.02124 [a]	–3.5800 [a]	0.34964 [a]	13.519 [a]
	(0.00534)	(0.00798)	(0.22972)	(0.00798)	(0.9732)
Sorghum					
Linear	0.00028 [a]	0.01431 [a]	–0.07847 [a]	0.03925	8.7116 [a]
	(0.00003)	(0.00015)	(0.00041)	(0.00030)	(0.0291)
Cobb-Douglas	0.2373 [a]	0.48029 [a]	–2.5633 [a]	0.55248 [a]	11.238 [a]
	(0.00672)	(0.00399)	(0.05870)	(0.00269)	(0.2211)
Soybeans					
Linear	–0.00006 [a]	–0.02048 [a]	–0.16895 [a]	–0.00148 [a]	5.0756 [a]
	(0.000001)	(0.00021)	(0.00139)	(0.00033)	(0.01035)
Cobb-Douglas	0.0210 [a]	0.8194 [a]	0.0586 [a]	0.2028 [a]	0.4920 [a]
	(0.00356)	(0.02242)	(0.00267)	(0.00846)	(0.0803)
Wheat					
Linear	–0.00003 [a]	–0.06201 [a]	–0.00167 [a]	0.05412 [a]	6.4186 [a]
	(0.000001)	(0.00006)	(0.00015)	(0.00015)	(0.01034)
Cobb-Douglas	0.14732 [a]	–1.6473 [a]	5.0875 [a]	–2.1145 [a]	–8.8744 [a]
	(0.01035)	(0.01493)	(0.24809)	(0.02403)	(0.9673)

Numbers in parentheses are standard errors.
[a] Significant at 99% confidence level.

Table VI

Elasticity of crop yield variance to a change in precipitation or temperature

Functional form for yield variability	Corn		Cotton		Sorghum		Soybean		Wheat	
	Precipitation	Temperature	Precipitation	Temperature	Precipitation	Temperature	Precipitation	Temperature	Precipitation	Temperature
Linear	–9.7187	7.5058	–0.3028	–10.9386	0.5230	–5.3517	–0.7932	–0.2739	–2.1572	–0.1035
Cobb-Douglas	–1.4461	0.8923	–0.0212	–3.5800	0.4802	–2.5633	0.8194	0.0586	–1.6473	5.0875

Linear elasticities are coefficients in Table V multiplied by average climate divided by average yield (see Figure 1).

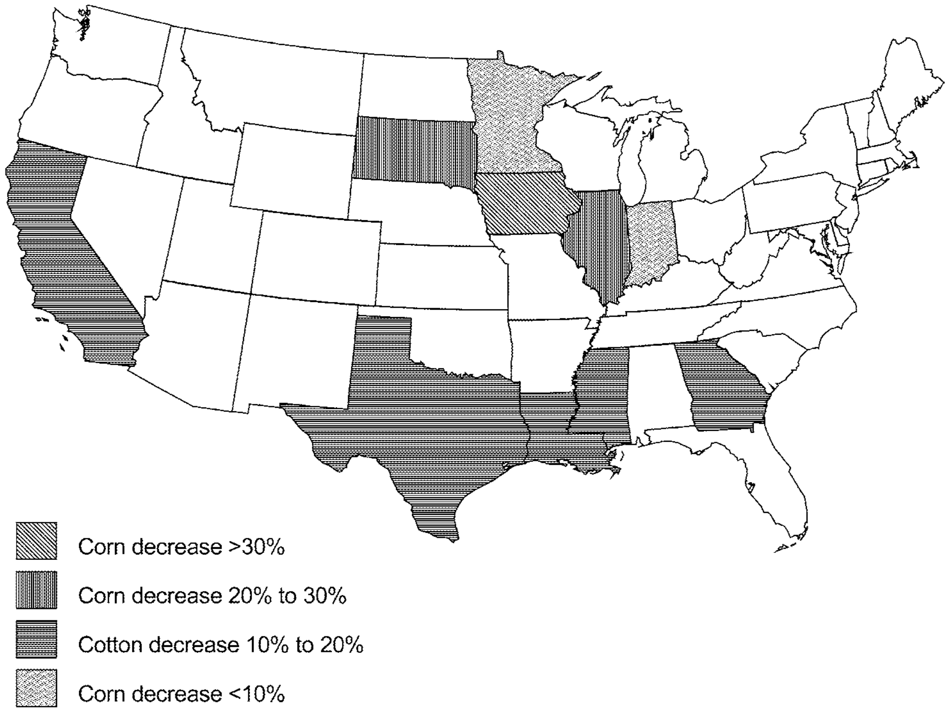

Figure 3. Percentage decrease in corn and cotton yield variability (for year 2090) under projection of climate change (Canadian GCM) from Table VII.

the estimated production function in the previous section. The climate change projections can be plugged into the variability estimates because they are constructed to be independent of mean changes in climate from the historical record.

The results are given in Table VII and show uniform decreases in corn and cotton yield variability of up to 25%, uniform increases in soybean yield variability and mixed results for sorghum and wheat. Figures 3 and 4 show the geographical relationship between different results and illustrate how consistent they are within regions (between nearby states). These results should be considered with some caution of course, because of the uncertain nature of projected future changes in climate (only two of many available climate scenarios have been presented) and the possible effects that future changes in climate variability could have on the yield distributions.*

* There is some evidence that intensification of the hydrological cycle at higher temperatures leads to increased weather variability that might have unforeseen impacts on crop yield distributions.

Table VII

Percentage increase in crop variability for year 2090 under alternative climate change projections from Global Circulation Models (GCMs) [a]

	Canadian GCM projection					Hadley GCM projection				
	Corn	Soybeans	Cotton	Wheat	Sorghum	Corn	Soybeans	Cotton	Wheat	Sorghum
CA			–12.84					–11.81		
CO					–13.35					–0.40
GA			–10.35					–6.92		
IL	–25.71	21.28				–24.73	18.90			
IN	–8.73	8.06				–26.31	20.30			
IA	–36.89	33.14				–26.83	20.90			
KS				–14.39	0.75				–18.16	3.38
LA			–13.03					–7.97		
MN	–2.87	4.01				–13.97	10.60			
MT				32.86					–6.36	
MS			–13.92					–7.73		
NE					–16.15					–1.72
OH		7.60					19.85			
OK				16.34	–9.27				–17.07	2.83
SD	–21.75			–6.94		–24.37			–19.10	
TX			–13.21	27.86	–10.83			–8.05	2.26	–3.10

[a] Neither of the regional climate change projections considered here include CO_2 fertilization effects. The size of these effects can be substantial in controlled settings, but regional long-term climate predictions usually do not distinguish regional differences in the impacts of CO_2 fertilization, reflecting the current state of scientific understanding of the phenomenon.

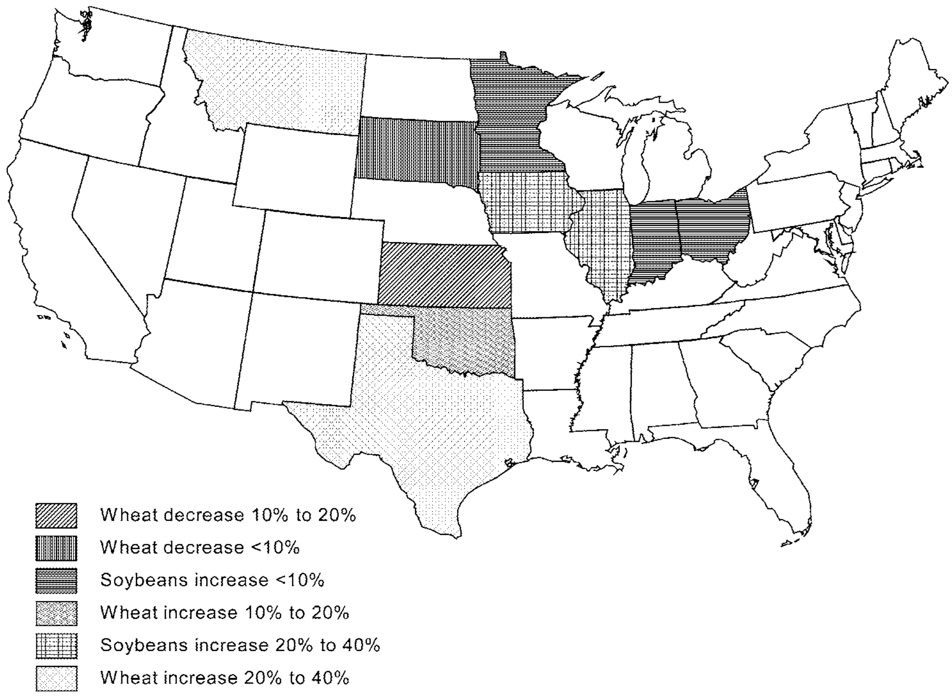

Figure 4. Percentage change in soybeans and wheat yield variability (for year 2090) under projection of climate change (Canadian GCM) from Table VII.

5.2. YIELD VARIABILITY OVER TIME

Thus far we have made use of the historical record in determining, among other things, the sign of the association between climate variables and inter-annual average and variance of crop yields. We then used climate change projections to see how much the historical record indicates that yield variability might change when forecasted out-of-sample. In addition to these results, we also determined from the historical record that the average and the variance of crop yields exhibited significant time dependence. Table III shows average yield increased over time while Table V shows in most of the cases that variability also increased over time. This is consistent with the assertions in a number of previous efforts, as collected in Anderson and Hazell (1987), that increased mean yields are associated with increased yield variability.

One interpretation of these results is that agricultural policy objectives such as farm income maintenance may not be working in concert with successful attempts to improve crop production technologies that have focused primarily on increasing average yields. From the standpoint of the out-of-sample forecasts, continued future trends toward increased yield variability could be quite disruptive if the climate change projections turn out to be accurate and new institutions have not been developed to deal with the added variability in farm yields. The Cobb-Douglas specification for cotton and wheat are the only two results that do not fit the pattern we describe and these anomalies may arise from the combination of a non-linear specification and the fact that yields for these crops have leveled-off or declined slightly.

6. Concluding Comments

This study has developed quantitative estimates of the impacts of annual average climate conditions on yield variability of major agricultural crops across the U.S. This is accomplished by estimating a Just-Pope stochastic production function using a time series and panel data set of U.S. crop yields for major crops by state. The results show changes in average climate conditions cause alterations in crop yield levels and variability. The effects are found to differ by crop. For corn, precipitation and temperature are found to have opposite effects on yield levels and variability. More rainfall causes corn yield levels to rise, while decreasing yield variance. Temperature has the reverse effects. For sorghum higher temperatures reduce yields and yield variability. More rainfall increases sorghum yields and yield variability.

An evaluation of the estimated results over climate change projections reveals how future projected climate change may influence yield variability. In particular, under the Canadian and Hadley scenarios used in the USGCRP national assessment, future variability decreases for corn and cotton while it increases for soybeans, while we find mixed effects for wheat and sorghum. Such results indicate directions that public or private breeding programs might need to take for the different crops if a future goal is to reduce variability while maintaining average crop yields.

Appendix A: Panel Unit Root Tests

The panel unit root tests we use are from Quah (1994), Im et al. (1997), and Levin and Lin (1992, 1993). Quah's test does not allow for region specific effects. Since we showed the importance of region effects in the paper, we rely on Im et al.'s test. Their test shows better finite sample performance than the tests due to Levin and Lin, in Monte Carlo simulations on panels with a large number of regions relative to the number of time periods.*

The test is valid when the errors in the region regressions are serially uncorrelated, and normally and independently distributed across regions. Under these circumstances their test statistic is distributed as standard normal as long as the number of regions (N) is large relative to the number of time periods (T). For

* Application of the Im et al.'s test to another data set can be found in Coakley and Fuertes. Heimonen uses Levin and Lin's test.

wheat, corn, and soybeans we have 25 annual observations with a few sub-state level observations. There are, e.g., 1400 observations for wheat, with 25 years of data across 56 regions. This is the widest panel, but for all the crops considered here, N is large relative to T.

Suppose that yield or climate, y_{it}, has a representation as a stochastic first-order auto-regressive process for region i and time period t,

$$\Delta y_{it} = \alpha_i + \beta_i y_{i,t-1} + \varepsilon_{it}\,, \quad i = 1, \ldots, N; t = 1, \ldots, T, \tag{A1}$$

where $\Delta y_{it} = y_{it} - y_{i,t-1}$ and ε_{it} are independently and identically distributed both across i and t. The null hypothesis of a unit root in (1) is then a test of

$$H_0 : \beta_i = 0 \text{ for all } i\,.$$

Appendix B: Fixed or Random Effects in the Panels of Data?

The time series properties of the variables are established in the paper, and this appendix takes the additional step of establishing if the individual panels of data have fixed or random state (individual) effects. The time series results indicated that some of the variables in Table I may have correlations across regions. To test for fixed or random region effects in the model, several approaches are available. Suppose a panel model with two-way error components is depicted as follows

$$y_{it} = \alpha + X'_{it}\beta + u_{it} \quad i = 1, \ldots, N; t = 1, \ldots, T, \tag{A2}$$

where $u_{it} = \mu_i + \lambda_t + v_{it}$, μ_i denotes the unobserved specific region effects, λ_t is an unobserved time effect, v_{it} is the disturbance term, and their variances are σ^2_μ, σ^2_λ and σ^2_v respectively.

The Breusch and Pagan test considers the null hypothesis that the variance of region and time specific effects is zero in (A1). Honda suggests a one-sided version of this test, which is preferred because of expected non-negative variance components. Honda's version of the test is a uniformly most powerful test of $H_0 : \sigma^2_\mu = 0$ vs. fixed effects. The test statistic (Baltagi, 1995, p. 62) is,

$$\sqrt{\frac{NT}{2(T-1)}}\left[\frac{\tilde{u}'(I_N \otimes J_T)\tilde{u}}{\tilde{u}'\tilde{u}} - 1\right] \xrightarrow{H_0} N(0,1), \tag{A3}$$

where N is the number of cross-sections (regions); T is the number of time-series observations; $\tilde{u}$ is an $NT \times 1$ vector of residuals; I_N is an $N \times N$ identity matrix; J_T is a $T \times T$ matrix of ones; $u_i \sim IID(0, \sigma^2_u)$, $v_{it} \sim IID(0, \sigma^2_v)$.

The results from the estimation of (A2), in the second row of Table II, indicate that the null hypothesis is rejected for all five equations, and a zero variance on the region effect is rejected with 99% confidence. These results indicate the existence of random region effects, information used in the specification of the production function.

Appendix C: Tests of Model Adequacy

This Appendix tests the adequacy of the panel production function models used in the paper. The classical assumption of the random effects model is that the errors are region specific. The significance of a deterministic time trend along with the other stationary variables leads us to consider if regional production function errors might also be time specific. If serial correlation was previously ignored, estimates in Table III could be consistent but inefficient, with biased standard errors. Log-likelihood values are presented in Table III, but because the mean and variance of crop yields are estimated simultaneously using maximum likelihood these diagnostic statistics also apply to Table V.

Since random region effects were shown to exist from the results in Table II, it seems appropriate to test for serial correlation jointly with this information. Baltagi and Li (1995) present a series of tests for serial correlation that are carried out jointly with various assumptions concerning region effects. Their Lagrange Multiplier (*LM*) test for zero first-order serial correlation assuming random region effects is the same whether the alternative is *AR*(1) or *MA*(1) (Baltagi, 1995, pp. 91–93), which is fortunate as we have no way of testing which is the appropriate alternative.

For *AR*(1) serial correlation, a new specification of the error terms in Equation (2) are as an *AR*(1) process with $v_{it} = \rho v_{i,t-1} + \varepsilon_{it}$, $\varepsilon_{it} \sim N(0, \sigma_\varepsilon^2)$. The null hypothesis is the restriction on this equation that $H_0 : \rho = 0$. The test statistic $LM = (\hat{D}_\rho)^2 \hat{J}^{11}$ is distributed χ_1^2 for large N, where

$$\begin{aligned}
\hat{D}_\rho &= [N(T-1)/T]\frac{\hat{\sigma}_1^2 - \hat{\sigma}_\varepsilon^2}{\hat{\sigma}_1^2} + \\
&\quad + (\hat{\sigma}_\varepsilon^2/2)\hat{u}' \left\{ I_N \otimes \left[\left(\frac{\bar{J}_T}{\hat{\sigma}_1^2} + \frac{E_T}{\hat{\sigma}_\varepsilon^2} \right) G \left(\frac{\bar{J}_T}{\hat{\sigma}_1^2} + \frac{E_T}{\hat{\sigma}_\varepsilon^2} \right) \right] \right\} \hat{u}
\end{aligned}$$

$$\hat{J}^{11} = N^2 T^2 (T-1)/\det(\hat{J}) 4 \hat{\sigma}_1^4 \hat{\sigma}_\varepsilon^4$$

$$\hat{\sigma}_\varepsilon^2 = \hat{u}'(I_N \otimes E_T)\hat{u}/N(T-1)$$

$$\hat{\sigma}_1^2 = \hat{u}(I_N \otimes \bar{J}_T)\hat{u}/N$$

$$\bar{J}_T = J_T/T,$$

$$E_T = I_T - \bar{J}_T\,.$$

and $\hat{u}$ are the maximum likelihood residuals under the null hypothesis. $\hat{J}$ is an information matrix while G is a bidiagonal matrix with bidiagonal elements all equal to one.

Test results for serial correlation are displayed in the third row of Table II, along with the Appendix A results. The results for serial correlation fail to reject the null hypothesis, indicating no serial correlation in the production functions for all five crops. Since the regional production function errors are not time specific, the standard errors of the estimates in Table III are correct.

Another assumption of the maximum likelihood models is that the error terms in each state are normally distributed. A standard test of this assumption is a Wald test derived by Greene (chapter 6) and the test statistic is

$$W = n\left[\frac{b_1}{6} + \frac{(b_2 - 3)^2}{24}\right] \sim \chi_2^2, \tag{A4}$$

where b_1 is a skewness coefficient, and b_2 is a kurtosis coefficient. Significant departures from the skewness and kurtosis of the normal distribution are indicated by a large test statistic, W, that is distributed chi-squared with two degrees of freedom. We reject the null hypothesis of non-normality with 99% confidence or greater for all crops in all states except cotton in Arizona, California and Missouri. Ranges of test statistics results across all states are reported in the last row of Table II. Moss and Shonkwiler (1993) find non-normality in U.S. corn yields, but since we do not find evidence of non-normality in the distribution of residuals we do not investigate further the possibility of yield non-normality.

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(Received 17 March 2003; in revised form 20 January 2004)